Exceeding the Threshold: Analysis of Public Information Transfer using Instrumental Variables

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Honors thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in the Trinity College of Duke University.

Duke University
Durham, North Carolina
2014

The Duke Community Standard was upheld in the completion of this assignment.

Acknowledgements

I wish to thank Professor Christopher Timmins for his extensive knowledge, support and advice throughout the creation of this paper. I am also especially grateful to Lala Xun Ma for her never-ending patience, encouragement and Stata expertise. I would finally like to thank Professor Michelle Connolly for her mentorship and insightful feedback over the past year and a half. Without all of you, this paper would not have been possible.

Abstract

This paper examines how information transfer about contamination levels found at brownfield sites capitalizes into nearby property values. More specifically, a hedonic model is used to test the impact on housing transaction prices when a binary measure (i.e. exceeding a threshold or not) or a continuous measure (i.e. chemical levels) is used. In the analysis, I exploit the variation in the contaminant thresholds, caused by regulatory conditions defined by the state of Massachusetts, holding the contaminant level constant. As thresholds are tied to neighborhood attributes in areas surrounding brownfields, threshold exceedance is potentially correlated to unobserved factors that impact housing values. An instrumental variables approach is used to create variation in threshold exceedance through the use of an instrument that measures the presence to underground aquifers. After instrumenting for threshold exceedance, my estimates indicate that a 10.8% decrease in housing values occurs when a contaminant threshold is exceeded, while the continuous measures of toxicity indicate a negative but insignificant effect. These findings suggest that policy makers should consider information conveyance when creating policies to inform homeowners of pollution presence, as improved information provision may increase public awareness about local environmental concerns.

JEL Classification: C26, Q53, Q58

Keywords: brownfields, pollution, housing markets, hedonic analysis, instrumental variables

1 Introduction

Environmental policy often aims to combat externalities and alleviate threats to the biophysical environmental, including to human welfare. To achieve the successful integration and benefits of such policies, especially related to pollution and toxic waste, public information transfer on environmental quality is of the utmost importance. Firstly, access to improved information allows households to make more informed decisions and adjust their behavior to reduce pollution exposure (Viscusi et al 1986, Smith and Johnson 1988, Graff Zivin et al 2011, Graff Zivin and Neidell 2009). Secondly, information provisions can incentivize firms to reduce output waste as a response to household demand for improved environmental quality (Hamilton 1995, Konar and Cohen 1997, Khanna and Damon 1999, Powers 2013). Thus, policy related to pollutant information release concerning potential threats to community residents should be thoughtfully considered and legislated.

Due to the importance of information transfer, research examining the relationship between pollutant contamination and housing transaction price has become prevalent in the past decade. Considerable research has been undertaken on household demand for environmental quality including the analysis of changing risk perceptions as a reaction to changing information (McClelland et al 1990, Gayer and Viscusi 2002, Bui and Mayer 2003, Decker et al 2005, Oberholzer-Gee and Mitsunari 2006, Sanders 2013) to test whether neighborhood pollution levels are capitalized into housing markets.

The majority of papers on this topic show that contaminant information negatively affects housing prices when risk perceptions increase after the information release. While these findings are generally consistent, the methods for information release vary. These methods include public administrative data on toxins released (Bui and Mayer 2003, Decker et al 2005, Oberholzer-Gee and Mitsunari 2006, Sanders 2013), newspaper coverage (Gayer and Viscusi 2002), direct solicitation from households (Gawande and Jenkins-Smith 2001), and environmental site or risk assessments (McClelland et al 1990, Ma 2014). The possibility that households assess types and methods of information transfer differently has also been analyzed by looking at information release from the Toxic Inventory Release (TIR) program (Bui and Mayer 2003). They find that increasing information provision had no impact on housing prices, which was attributed to the fact that individuals could not comprehend the complexity of the information given. Thus, from a policy perspective, it appears that information transfer regarding contamination should be simple and direct so that the public can make informed decisions based on their perceived safety.

This paper aims to contribute to the literature regarding environmental information provision through the examination of the effectiveness of a binary measure (i.e. a threshold) in information transfer. More specifically, I collect data from the State of Massachusetts (MA) on individual chemicals found at brownfield sites, which are defined by the U.S. Environmental Protection Agency (EPA) as industrial and commercial areas that contain one or more hazardous substances, pollutants or contaminants. I then compare this to the threshold value determined by MA regulatory provisions in order to assess the toxicity for each chemical, and subsequently for the entire site. By doing this I can exploit the variation in contaminant threshold values, which are based on regulatory requirements for brownfield sites in MA. As the variation in threshold levels is tied to neighborhood characteristics such as proximity to schools and hospitals, threshold exceedance may be correlated with unobserved neighborhood characteristics that also impact housing values. To overcome this, I use brownfield proximity to an underground aquifer as an instrument to ensure exogenous variation in threshold exceedance.

2 Literature Review

2.1 EPA Brownfield Program

Over the past few decades, federal, state and local governments have put increased resources into combating pollution and rehabilitating neighborhoods where pollutants are found. Specifically, areas that contain polluted brownfield sites are often abandoned or underutilized, despite the fact that they pose a relatively low risk to nearby residents. These sites are seen as unattractive places to live and work, making them prime targets for remediation. Remediation efforts can be of great benefit to economically depressed areas, as a non-performing piece of real estate is converted into a productive entity.

Survey research on brownfield sites labeled Temporarily Obsolete Abandoned Derelict Sites (TOADS) found that people have a negative perception of local environments where brownfields exist, leading to a decline in business and residential interest. In these areas, illegal activities such as waste dumping and drug abuse are also more likely to occur, further stigmatizing the neighborhood (Greenburg et al. 2000). Market-based incentives were also analyzed to determine benefits of brownfield cleanup. While contaminated sites were deemed less attractive by a survey of real estate developers, regulatory relief was found to influence land utilization (Alberini et al. 2005).

These studies confirm investor worries regarding hidden costs and highlight the importance of remediation action on brownfield sites.

The United States Environmental Protection Agency Brownfields Program aims to identify and clean up brownfields in the hopes of improving neighborhood aesthetics and value. This program was instituted in 1995, at which time the EPA began providing grant funding to organizations looking to revitalize brownfields for environmental, social and economic benefits. In 2002, the Small Business Liability and Brownfields Revitalization Act, or "Brownfields Law", was signed, increasing financial funding for brownfield remediation. The U.S. Government Accountability Office (GAO) estimates that there are over 450,000 brownfield sites in the United States, with others that have not yet been recognized.

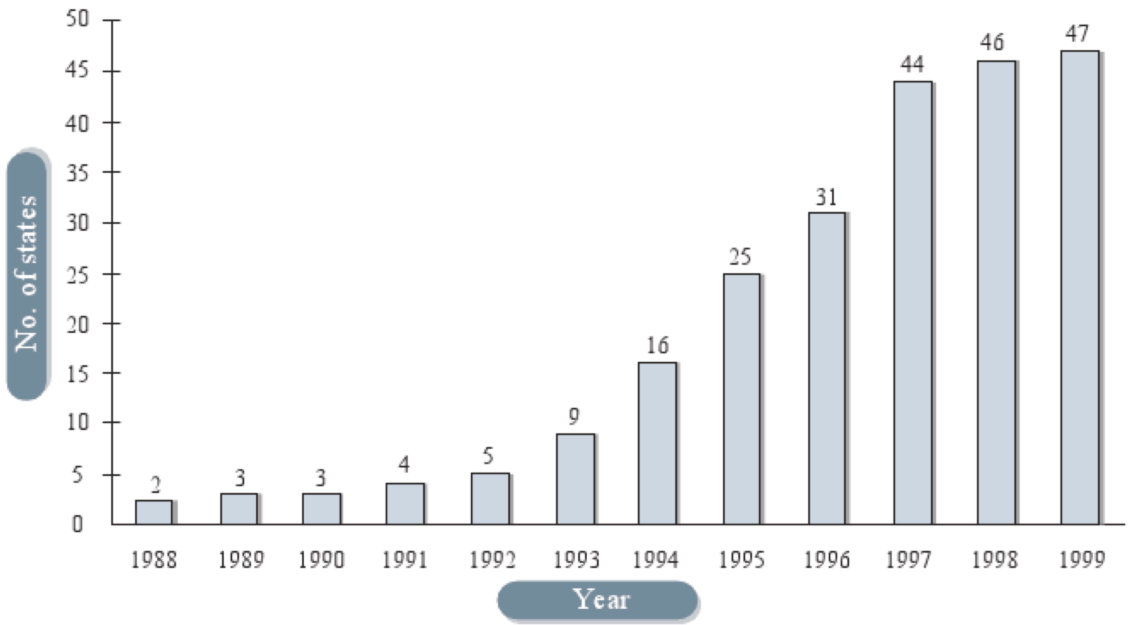
The grants given by the Brownfields Program vary in size and type, depending on the condition of the site and the community's level of need. In total, there are four types of grants designated: assessment grants, job training grants, cleanup grants and revolving loan fund grants. Each grant serves a different purpose for the community; however all represent important aspects of remediation efforts. These grants typically provide up to $200,000 for their specified purpose. Assessment grants are the most common type of grant awarded, providing funds to be used for planning a brownfield cleanup. On the other hand, funds allocated to job training grants are the least common, and are used to find and train unemployed and low-income residents from local areas to assist with the site cleanup. Cleanup grants remediate brownfields that have been exposed to petroleum or hazardous pollutant contamination. Finally, revolving loan fund grants help to capitalize a revolving loan fund, providing loans and sub-grants for clean up processes.

Overall, from 2002- 2011, the U.S EPA paid over $670 million for brownfield grants, $331.3 million for 1,479 assessment grants, $25.2 million for 121 job training grants, $150.7 million for 801 cleanup grants, and $167.5 million for 143 revolving loan grants. However, even though this money designated for cleanups is a good starting point, data compiled from the Council for Urban Economic Development (CUED) and the EPA show that in 1999 brownfield cleanups were estimated to cost an average $780,000 per site (Paull 2008). This amount is significantly higher than the typical $200,000 grants provided by the EPA, especially when inflation and conversion to 2014 dollars brings the amount closer to an estimated $1.1 million dollars.

Despite the associated financial costs, brownfield cleanups have been found to be beneficial to communities and residents for multiple reasons. Not only does cleanup improve environmental factors including adverse effects caused by the pollutant, but it also helps to promote economic growth in urban areas. Overall, brownfield remediation can help economic development, protect public health, revitalize neighborhoods, create jobs and grow the tax base (Pepper 1997). Nonetheless, investors often fear the liabilities associated with developing a contaminated site and the high costs associated with remediation. This is especially relevant as it can be difficult to determine the specific set of pollutants found at the site, leading to additional costs for investigation and repeated remediation. Other obstacles to brownfield cleanup include lack of capital, community concerns, liability issues and environmental policy regulations.

In recent years, states have realized the value of cleanup efforts, even if complete elimination of pollutants has not been achieved. Thus, many states have adopted a "risk-based approach," emphasizing risk assessment and management. This means that they accept the presence of certain contaminants, as long as human exposure and environmental risk is eliminated. Because of this, over time the number of voluntary state brownfield cleanup programs has grown exponentially (Rakestraw 2000).

Figure 1: Growth of Voluntary State Brownfield Cleanup Programs Over Time



2.2 Contamination Reporting in Massachusetts

In 1986, the Emergency Planning and Community Right-to-Know Act (EPCRA) was enacted, establishing reporting requirements to provide the public with better information regarding hazardous chemicals present within local communities (U.S. EPA 2014). It is important to note that the EPCRA does not place limits on what chemicals can be used at any facility, instead transforming the documentation and notification process associated with contaminant information release. This policy is effective in all states, for all sites where hazardous chemicals are present, including brownfield sites.

In Massachusetts, brownfield sites are assessed and contamination levels are measured by the Massachusetts Department of Environmental Protection (MA-DEP). This is a formal process that analyzes sites based on a handbook known as the Massachusetts Contingency Plan (MCP). Each assessment is undertaken by a licensed environmental professional, who collects and analyzes samples of soil, groundwater, air and sediment. The tested contaminant levels are then compared to a threshold that is specific to each individual chemical based on toxicity, human threat and neighborhood characteristics.

More specifically, stricter threshold standards for a given site will hold if there is a residential population within one mile, institutions such as schools, hospitals and community centers within 500 feet, on-site workers, if the site is on an aquifer, or if within 500 feet of a drinking water source. Thus, a threshold level will be lower if there are higher risks of human exposure (e.g. school) or a greater potential to cause environmental harm (e.g. wetland). Specifically in Massachusetts, these standards are defined as GW-1 through GW-3 for groundwater, with GW-1 being the highest threshold, and S-1 through S-3 for soil, with S-1 being the highest threshold.

2.3 Hedonic Analysis

Hedonic pricing models have been used to analyze the impact of diverse environmental factors on housing values. Hedonic analysis has its roots in the theory of value developed by Lancaster in 1966, which explains commodity value as a collection of characteristics. Ridker and Henning first applied this method to environmental research in 1967, looking at the effect of air pollution on property values in St Louis. The pair found a negative relationship between housing price and sulfate air measures.

In 1974, Rosen explored the use of hedonic prices to estimate the value of specific amenities, such as environmental quality. His work was essential as it set up a theoretical framework for recovering the marginal willingness to pay (MWTP) from a hedonic price regression by specifying the relationships between consumer preferences for specific characteristics and the price function, also known as hedonic equilibrium.

Hedonic models have been used in many different contexts to value household preferences for environmental and non-environmental factors. A hedonic framework was employed when estimating the value residents place on living away from Superfund hazardous waste sites in order to minimize cancer risks (Gayer, Hamilton and Viscusi 2000). Residents are willing to pay the most to avoid risk before the remedial investigation documentation is released, informing residents of composite risk. The amount that they are willing to pay to leave the polluted neighborhood declines after they are aware of the size of the risk, presumably because the information released lowers perceived levels of hazard.

The valuation of brownfield sites, which is the application of a hedonic framework used in my paper, has been used to look at the change in property values after brownfield remediation has occurred (Haninger et al. 2013). Large increases in property price are realized following a brownfield cleanup, ranging from 4.0% to 24.8%. Another hedonic analysis looked at Kenosha, Wisconsin and analyzed the response of property values to local brownfields (Kaufman and Cloutier 2006). It was estimated that a brownfield cleanup would increase property values for 890 homes between $2.4 and

$7.01 million. The focus of these analyses was on the benefits of a brownfield cleanup on the neighborhood housing markets. In my analysis, I only examine sites that have not yet experienced a cleanup, but fulfill the eligibility requirements and have submitted a cleanup grant application to the state of Massachusetts.

The effect of a nearby brownfield site on home prices in Atlanta and Cleveland was also analyzed using a hedonic model (Leigh and Coffin 2005). The presence of a brownfield is found to lower property values, with the highest impact falling on those who live within 500 feet of a brownfield. This model differs from what I will undertake, as in this analysis site pollutants and thresholds were not taken into consideration, meaning that all brownfield sites were considered to have an equal impact on housing transaction price.

3 Model Specifications

3.1 Hedonic Regression

In my paper, a hedonic model was utilized to analyze property valuation and information transfer to residents living near brownfield sites. A hedonic model can be used where product variety within the same market gives rise to price differences that can be analyzed in market transactions. By observing the choices consumers make with regards to differing characteristics and prices of goods, the implicit price of one component can be estimated. However, as brownfield remediation is not an item traded in markets, I must infer its value based upon housing transactions in the surrounding neighborhood.

In a hedonic regression, few guidelines exist for determining the influence of individual characteristics, however each variable must be noted for its effect on price. In its simplest form, the hedonic price function is a linear regression. However, marginal prices are unlikely to remain constant for all characteristics. Thus, several functions exist for evaluation based on specific attributes

Table 1: Table of Possible Hedonic Functions

Name	Equation	Implicit Price
Linear	$P = \propto_0 + \sum \beta_i z_i$	$\frac{\partial P}{\partial z_i} = \beta_i$
Semi Log	$\ln(P) = \propto_0 + \sum \beta_i z_i$	$\frac{\partial P}{\partial z_i} = \beta_i P$
Double Log	$\ln(P) = \propto_0 + \sum \beta_i ln(z_i)$	$\frac{\partial P}{\partial z_i} = \beta_i {}^{P}/_{z_i}$
Quadratic	$P = \alpha + \sum_{i=1}^{N} \beta_i z_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \delta_{ij} z_i z_j$	$\frac{\partial P}{\partial z_i} = \beta_i + \frac{1}{2} \sum_{j=1} \delta_{ij} z_j + \delta_{ij} z_j$

The hedonic method is most commonly applied to housing market analysis, in which house structure, land amenities, neighborhood attributes and geographic location must be taken into consideration. In my analysis, factors that may influence housing price include house, site, neighborhood and environmental quality characteristics, such as the number of bedrooms, square footage of the house, neighborhood crime rates, and percentage of low-income families in the neighborhood.

For my analysis, the hedonic function is in a semi log form. I model the price of a property, *P*, that is located in district, *j*, near brownfield site, *m*, as the following

$$\ln P_{ijmt} = \propto_0 + \beta_1 \, maxtox_{mt} + \beta_2 \, exceedthreshold_{jmt} + \varepsilon_{ijmt}$$

where ε_{ijmt} is an idiosyncratic shock that is specific to the property at time *t.* To examine whether consumers care about the actual toxic threat of a brownfield site, or simply whether a threshold has been exceeded, $maxtox_{mt}$, which refers to the maximum toxicity found at the brownfield at time *t,* and $exceedthreshold_{jmt}$ are used. $Exceedthreshold_{jmt}$ is set equal to one if a particular house in district j, within 3km of a site m, has any contaminant exceeding a threshold at the time when a report was compiled. This variable allows for adequate examination of the impact of any chemical exceeding the assigned threshold value.

The hedonic price function yields estimates of implicit prices of attributes that can be used to uncover consumer preferences. Consumers want to maximize their utility $U\ (\underline{Z}, x;\ \alpha)$, where $\underline{Z}$ is a vector of characteristics of a property, x is all other goods, α are the household characteristics and y is income

$$\mathrm{L} = \max u\ (\underline{Z}, x;\ \alpha) + \ \lambda\ (y - x - P\big(\underline{Z}\big))$$

The first order conditions derived from this problem imply that $\frac{\frac{\partial u}{\partial z_i}}{\frac{\partial u}{\partial x}} = P_z(\underline{Z})$. This represents the tangency point of the individual's indifference curve map and budget constraint, where the indifference curve is: $u\big(\underline{\mathrm{Z}}, x;\ \alpha\big) = u_0$. This is combined with the budget constraint, implied by the hedonic price function.

The hedonic price function shows how the price of a house varies with given attributes, with the slope giving the implicit price of the attributes as well as the marginal willingness to pay for the consumer who purchases that level of attributes. However, it is important to note that the individual demand curve for the attribute cannot be estimated without more data and theory, as the marginal willingness to pay (MWTP) is known at only one point.

My analysis implements the hedonic method, and is based upon the idea that a homeowner's disutility from living near a brownfield site can be measured by comparing differences in housing values. The homeowner's marginal willingness to pay (MWTP) to live further from a brownfield site can be read off of the hedonic gradient, or the derivative of the hedonic price function.

One issue with the hedonic approach is that all health hazards from living near a brownfield site may not be apparent, and thus will not be reflected in housing transaction data. However, due to the low risk nature of brownfield sites, especially when compared to other environmental pollutant sites (Superfund sites, TSDFs etc.) the risk of unknown health hazards is probably slim.

As I cannot guarantee that my estimates are not being confounded by unobserved factors, both year and district fixed effects are used in my analysis. Fixed effects essentially take the neighborhood means of each attribute being analyzed, and create mean-differenced data in order to control for permanent unobservable differences between neighborhoods surrounding brownfields. Assuming that the idiosyncratic error term is decomposed into district-specific fixed factors, μ_j, and brownfield- specific, time-varying factors, v_{mt}:

$$\varepsilon = \mu_j + v_{mt} + \bar{\varepsilon}$$

Then fixed effects removes the unobserved district-level factors, μ_j, that may confound estimates.

3.2 Instrumental Variables

Endogeneity issues arise with the variable describing threshold exceedance, as this variable may be correlated with unobserved neighborhood characteristics that also impact housing transaction price. Thus, an instrumental variable (IV) approach is used to alleviate the correlation of the variable *exceedthreshold* with the error term, ε. Using IV allows for the isolation of the variation in *exceedthreshold* that is uncorrelated with ε, thus disregarding the piece that causes bias in the OLS and FE estimates. To achieve this, I use an instrument, *aquifer,* that is correlated with price only through *exceedthreshold*, and is uncorrelated with ε, defined as:

$$aquifer = \begin{cases} 1 & \text{if brownfield to aquifer distance} = 0 \\ 0 & \text{otherwise} \end{cases}$$

Because the presence of an aquifer is used to determine the threshold value for each contaminant, it is directly correlated with the *exceedthreshold* term. Specifically, if a brownfield is situated above an aquifer, threshold values will be lower, and it is more likely that a threshold will be exceeded. Thus, the instrument easily satisfies the relevance condition, that:

$$Cov\ (aquifer, exceedthreshold) \neq 0$$

Proving the instrument's exogeneity, or $Cov\ (aquifer, \varepsilon) = 0$ is challenging due to the difficulty of demonstrating that aquifer location is not correlated with unobservable factors. However, as aquifers are located underground, this suggests that individuals may not even be aware of their property's proximity to one. Thus, *aquifer* is a stronger instrument than, for example, distance from schools, as it should not be correlated with neighborhood factors that affect housing prices, as a school would be.

Also, while exogeneity cannot be formally tested, balance tests provide further evidence for the validity of *aquifer* as an instrument (Gayer and Viscusi 2002). By collecting data on housing attributes, differences between treated groups (brownfield sites exceeding thresholds) and control groups (brownfield sites that do not exceed thresholds) can be analyzed. The differences in means of observable housing attributes, combined with observable neighborhood attributes, are tested to verify that the data are not statistically different across the instrument. If I fail to reject the balance t-test, this means that the difference in the means of observed attributes between houses located on an aquifer and houses not located on an aquifer is statistically undistinguishable from zero. Thus, the attributes are "balanced", meaning that the treatment and control groups can be considered the same. This analysis provides further verification of the exogeneity of the instrument.[*]

The IV approach is carried out using the two stage least squares (2SLS) estimator. This method decomposes *exceedthreshold* into two components, and uses the component not correlated with ε to estimate the *exceedthreshold* coefficient. The first stage assumes that there is a regression that links *exceedthreshold* and the instrument, *aquifer:*

$$exceedthreshold_{jmt} = \propto_0 + \beta_1 aquifer_i + \beta_2\, maxtox_{mt} + \varepsilon_i$$

[*] One concern with the *aquifer* instrument is that it may be negatively correlated with areas that are serviced by piped water (PWSA). These PWSA's in turn are most likely correlated with house price, as houses that have a piped water system will probably be considered more valuable by homeowners. To test this, I obtained known locations of the PWSA's from the Office of Geographic Information, which were recorded when MA began a project that interviewed public water suppliers around the state. However, due to funding issues this project was halted after data was compiled for 131 cities and towns in the eastern region of the state. Therefore, this presents an issue with inferring data about other regions and is not used in my analysis. In order to obtain definitive results and complete data, collaboration with the state department is needed and will take additional time to recover data maps.

Next, in the second stage, the uncorrelated component of *exceedthreshold* is used to estimate price by replacing $exceedthreshold_i$ with $\widehat{\propto_0} + \widehat{\beta_1} aquifer_i$, where $\widehat{\propto_0}$ and $\widehat{\beta_1}$ recovered using the OLS estimates from the regression above.

4 Data

4.1 EPA Data

In order to complete my analysis, housing transaction data from Dataquick Information Services is examined and combined with pollutant data available from the US Environmental Protection Agency (EPA).

The pollutant threshold and site contaminant levels were personally collected from reports released by the U.S EPA. Each of the 66 MA brownfield sites in my analysis are associated with between 1 and 9 reports, depending on how many times pollutant contamination levels have been measured. These reports vary from 100 to 700 pages in length, consisting of written analyses describing site history and findings, tables of chemical breakdown, and maps outlining geographic and land conditions. The EPA lists not only the concentration of pollutants at these sites, but also determines whether certain pollutants cross thresholds and constitute risks. For the sites with multiple brownfield assessments over numerous years, differing contaminant values over time are recorded as individual data points.

Specifically, this EPA data set includes variables for the date that the assessment was completed and breaks down contaminants by where on the site they are found- soil, sediment, surface water, ground water, air or other. Most sites collected pollutant concentrations for soil and groundwater, while air and sediment data were sporadically collected when there was a perceived threat. The majority of sites reported soil and groundwater from 4-10 locations on the site to examine differences in pollutant concentrations. In my analysis, the chemical concentrations from these different site samples are compared, and the highest concentration is recorded and assessed against the threshold value. The maximum concentration value is used as it is the most concerning to residents. In order to account for thresholds exceeded by contaminants, a variable labeled "toxicity" is calculated as the maximum concentration value divided by the threshold level, giving the relative danger of that contaminant. Any toxicity over 100% therefore indicates exceedance of the threshold for that given contaminant.

Thresholds are used in my analysis as they indicate whether there is a price differential between homes with the same pollutant concentrations and differing pollution threshold labels. In general, thresholds may be more important than pollutant concentrations as the public is notified of exceeded thresholds levels by mail or public newspaper announcement. Whether the contaminant level exceeds the threshold level is analyzed with the hedonic model. This allows for determination of the full risk posed by the pollutants and the true effect of higher contaminant levels relative to the threshold.

One issue with specific contaminants relates to differences in public perceptions. For example, a given household may have an irrational fear of lead near their home due to media-influenced perceptions, while an unknown polycyclic aromatic hydrocarbon could be more toxic. In my analysis it is difficult to measure whether housing transaction price is greatly affected by one contaminant over another due to public perception.

4.2 Housing Data

The Dataquick data set was purchased by the Duke Economics Department and provides information about housing transactions surrounding brownfield areas. This includes historical transaction data on the house, as well as attribute data recorded from tax assessments. Thus, information such as zip code, county name; information on whether primary property owner is an individual; a company or a trust; the value of the property according to the tax assessor (used to compute amount of taxes to be paid); the square footage; if the home contains a fireplace, garage, carport, porch or a pool; the number of bedrooms and bathrooms in the home; the year in which primary structure on property was built; and the year in which any major renovations were made to the property are noted.

Of these data, the most important for the regression analysis is the housing transaction price. Thus, any house that is missing its sale price is removed from the data set. House prices are normalized using the All Urban Consumers Housing CPI based on January 2000 levels given by the United States Bureau of Labor Statistics. This adjustment allows for direct comparison between housing transaction prices, without inflationary or deflationary effects over time.

The year in which renovations are made are also taken into consideration, as any major renovation made after the brownfield site assessment may drastically change the house characteristics and value, making data on previous sales inaccurate. Because of this, these houses are not included in the data set. Houses with missing information for bathrooms, bedrooms or square footage are also removed. Concerns of self-selection bias surrounding houses with missing data are minimal as the information is reported by an employee from the county assessors office and not the homebuyer or seller, which suggests that missing observations are typically random. Houses that are further than 3km from a brownfield site are also excluded in order to minimize issues associated with location-specific unobservable differences.

One major issue with the Dataquick data is that the analysis looks at a period of time beginning January 2, 1998 and ending October 5, 2012. As brownfield contamination data begins in approximately 1989, the housing data is not as expansive. Therefore, the earlier EPA contamination data cannot be taken into consideration. The set of brownfields under consideration are therefore those that were examined between 1998 and 2012, that have housing transaction data within 3km, that did not experience any form of clean up and that have detailed reports with specific dates and contaminant data, resulting in 66 unique brownfields in Massachusetts.

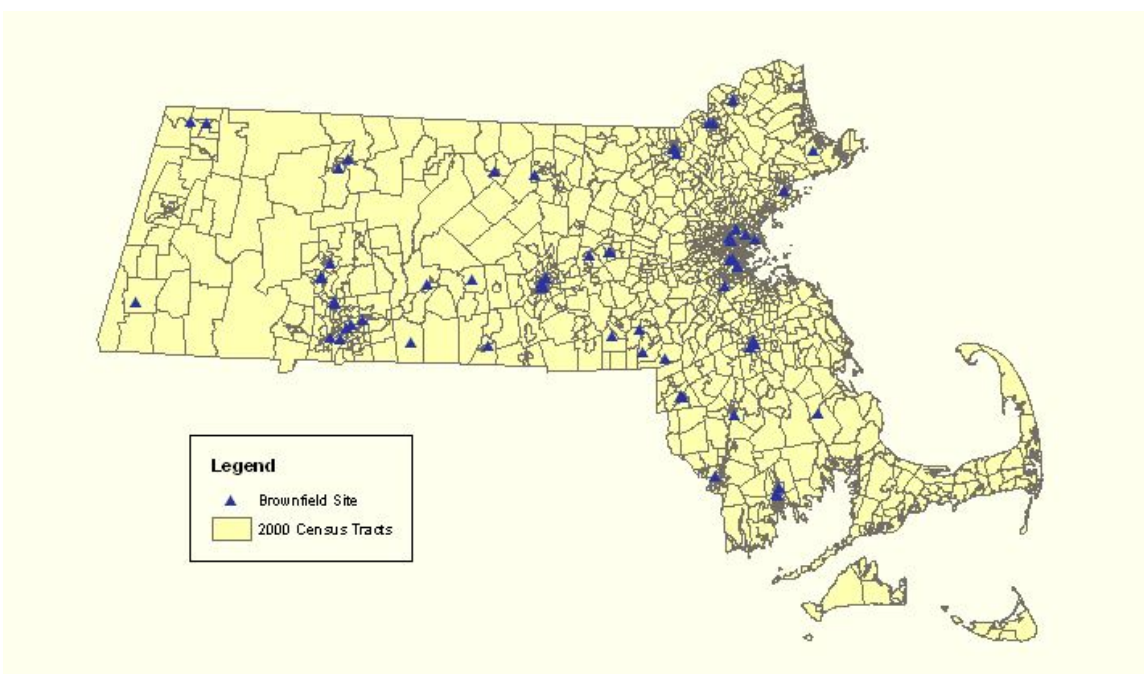
4.3 Graphical Information System

Districts are defined as areas where "public education services [are provided] for the area's residents" (U.S. Census Bureau). In Massachusetts, there are 224 defined districts, and information on crime, school quality and income for each district is reported. Of these 224 districts, 89 are examined after limiting houses to those within 3km of sites.

Specifically, to measure school quality, the percentage of students that obtain a score of proficient or advanced on the Massachusetts Comprehensive Assessment System (MCAS) in each school district is measured. On this test, four scores are possible: advanced, proficient, needs improvement and warning/fail. This information, as well as that on percentage of low income residents in each district and crime measures can all be found at the Mass.gov website.

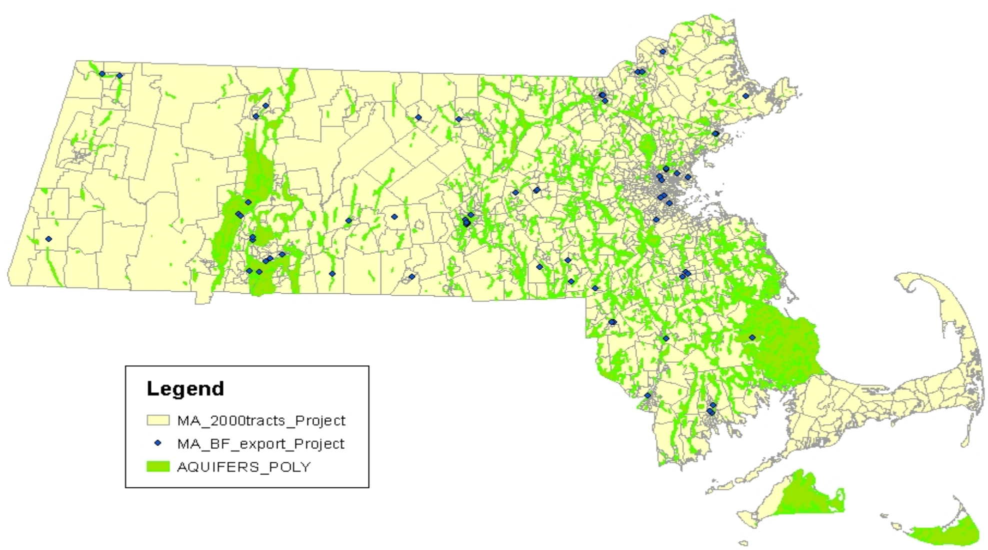
As the exact location of each house and each brownfield is known, the longitudes and latitudes from each site were used as inputs into graphical information system (GIS). Thus, the distance between each house and the nearest brownfield was calculated, dropping houses that lay outside of a 3km radius. In some cases, homes are found to be within radius of multiple brownfields, with some households being within 3km of 6 sites. To account for this additional pollution threat, homes that had more than one brownfield within the 3km radius were dropped from my analysis. Figure 1 illustrates a map of Massachusetts outlining the precise location of these brownfield sites within census tract lines.

Figure 1: Massachusetts Brownfield Sites within Census Tracts



Similarly, GIS was utilized when determining the locations of aquifer sites. The brownfield map in Figure 1 was overlaid on a map denoting the locations of aquifers in Massachusetts. Figure 2 illustrates the map of Massachusetts outlining the location of aquifers in relation to brownfield sites within census tract lines. This new map was then used to determine the distance from each brownfield site to the nearest aquifer, which assisted in the creation of the dummy variable *aquifer*, set equal to one if the distance from the aquifer to the brownfield is equal to zero.

Figure 2: Massachusetts Aquifer Sites within Census Tracts



4.4 Other Data

For the 66 brownfield sites analyzed, information exists outlining whether a site was eventually awarded a cleanup, the site proposal score, and the grant application type (petroleum, hazardous substances or both). These three factors were all set as controls in the analysis. The majority of brownfield sites (~80%) have contaminant data spanning across multiple years, with 292 unique chemicals found across all sites. Table 8 in the Appendix lists all chemicals found as well as their frequency. It is important to note that every site is not tested for every chemical. This is because some chemicals, such as pesticides, are only produced or used in certain industrial sites, and thus would not be present in all brownfield locations. Approximately 9,000 data points are recorded as the maximum concentrations of unique chemicals at all sites in all mediums.

Initially, the 292 chemicals were classified into 20 groups, including post transition metals, transition metals, xylenes, ringed polyaromatic hydrocarbons and napthalenes. Table 7 in the appendix illustrates the chemical groups created, outlined by the threshold exceedance found for each group. This breakdown based on chemical structure resulted in co-linearity issues between multiple variables, potentially due to companies using certain chemicals in sites that are complementary, despite differing chemical composition. Thus, maximum toxicity values are taken without regard for the chemical structure of the contaminant.

The final dataset defines one observation as one housing transaction. Housing characteristics are noted for each property, as well as transaction price, date of sale, and information pertaining to the local brownfield site, including maximum toxicity and whether a threshold is exceeded. For each house, distance to the nearest brownfield site is also noted after utilization of GIS software if the site falls within the designated radius of 3km.

District fixed effects are also used to control for time-invariant factors that are unobservable within neighborhoods. Year fixed effects and district fixed effects absorb the across-group observable and unobservable predictors, allowing for an improved analysis of the within-group action. This also minimizes the likelihood of omitted variable biases arising from year or neighborhood differences.

5 Results

Table 2 below shows summary statistics by house, neighborhood and brownfield attributes. The mean housing transaction price from 1998 to 2012 in Massachusetts falling within 3km of a brownfield site was $221,647.30 with a standard deviation of $140,491.30 after price deflation by CPI. There are 290,770 values for housing transaction price. Summary statistics show that the median *maxtox* value is 3.92, meaning 392% toxicity over threshold values, making this value economically significant. Further summary statistics of assessment results can be found in Table 9 in the Appendix.

Table 2: Summary Statistics

A. House Attributes

Variable	N	mean	p50	sd	min	max
Price	290770	221647.30	189770.60	140491.30	21967.15	1166016.00
# Bathrooms	290770	1.77	1.50	0.89	0.00	90.00
# Bedrooms	290770	3.04	3.00	1.66	0.00	128.00
Sq. ft.	290770	1690.85	1447.00	1149.68	0.00	32410.00
Year Built	288215	1946.35	1953.00	42.32	1650.00	2012.00
Condo	290770	0.29	0.00	0.45	0.00	1.00
Single Family	290770	0.56	1.00	0.50	0.00	1.00
Age	288215	57.17	51.00	42.36	0.00	350.00

B. Neighborhood Attributes (By School District)

Variable	N	mean	p50	sd	min	max
% Low income	89	24.26	17.00	21.46	0.80	87.10
% Crime	88	0.00	0.00	0.00	0.00	0.02
% Proficient or Advanced	89	47.46	46.00	23.44	9.00	88.00
C. Neighborhood Attributes (by Brownfield)						
Industrial activity nearby	58	0.45	0.00	0.50	0.00	1.00
Residential nearby	58	0.78	1.00	0.42	0.00	1.00
School nearby	58	0.59	1.00	0.50	0.00	1.00
Green nearby	58	0.60	1.00	0.49	0.00	1.00

Table 3 shows the results of the basic hedonic regression. House, neighborhood, district and brownfield characteristics are controlled for in Column (1), with Column (2) introducing district-level fixed effects. These results show that there is a negative and significant coefficient on *maxtox* in Columns (1). Additionally, it is seen that exceeding a threshold for any chemical causes housing prices to increase by 7.39% after controlling for neighborhood attributes, and 6.36% after incorporating district level fixed effects. This counter-intuitive result may be due to unobservable factors correlated with *exceedthreshold* and price, illuminating the need of an IV approach.

Table 3: Hedonic Price Regression

Dependent Variable: log (Price)	(1) OLS	(2) FE
exceedthreshold	0.0739***	0.0636***
	(0.0029)	(0.0031)
maxtox	-4.04e-10***	-2.16E-11
	(0.0000)	(0.0000)
distance to Brownfield	5.87e-05***	7.45e-05***
	(0.0000)	(0.0000)
# bathrooms	0.156***	0.130***
	(0.0017)	(0.0015)
# bedrooms	-0.0162***	-0.00799***

	(0.0009)	(0.0008)
sqft	0.000119***	0.000119***
	(0.0000)	(0.0000)
year built	-0.0509***	0.0122***
	(0.0012)	(0.0013)
age	-0.0508***	0.0112***
	(0.0012)	(0.0013)
condo	0.112***	0.143***
	(0.0038)	(0.0034)
single family	0.0407***	-0.0928***
	(0.0046)	(0.0042)
awarded	-0.0802***	-0.0375***
	(0.0052)	(0.0067)
proposal score	0.00725***	0.00552***
	(0.0001)	(0.0002)
hazardous substances	0.0950***	-0.118***
	(0.0074)	(0.0200)
petroleum	-0.126***	-0.118***
	(0.0065)	(0.0174)
property size (acres)	-0.00293***	0.0175***
	(0.0003)	(0.0007)
% Low income	0.00497***	0.000434
	(0.0001)	(0.0003)
% Crime	-7.912***	0.0995
	(0.4067)	(0.6570)
% Proficient or Advanced	0.0142***	-0.00254***
	(0.0001)	(0.0002)
Industrial activity nearby	-0.351***	-0.0928***
	(0.0030)	(0.0059)
Residential nearby	-0.0602***	-0.177***
	(0.0030)	(0.0045)
School nearby	0.0984***	0.0723***
	(0.0026)	(0.0040)
Green nearby	0.0761***	0.0691***
	(0.0031)	(0.0043)
Constant	111.9***	-13.30***
	(2.3697)	(2.5579)
Observations	150,430	150,430
R-squared	0.506	0.358
House Characteristics	X	X
Year Fixed Effects	X	X
Neighborhood Characteristics	X	X
District Fixed Effects		X

When examining house and district attributes by threshold exceedance in Table 4, significant differences are observed between houses sold near brownfield sites that exceed thresholds and those that do not. In the lower sections of the table, attributes are demeaned by district in order to incorporate fixed effects. This table illustrates that most differences in housing characteristics are rejected, however those that fail to be rejected do not present a major concern as they can be controlled for within the data. Overall, neighborhood attribute differences present more of an issue as they are more likely to bias the *exceedthreshold* variable.

Table 4: Attributes by Type

A. House Attributes

	exceedthreshold = 1			exceedthreshold = 0					
	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.	tstat	pval	Reject?
Price	215403.15	123752.52	125710	195149.77	108658.53	29244	-25.77	0.00	Y
# Bathrooms	1.78	0.90	125710	1.77	0.91	29244	-1.61	0.11	N
# Bedrooms	3.10	1.69	125710	3.05	1.61	29244	-4.53	0.00	Y
Sq. ft.	1703.18	1175.03	125710	1696.55	1067.49	29244	-0.88	0.38	N
Condo	0.23	0.42	125710	0.21	0.41	29244	-5.99	0.00	Y
Single Family	0.61	0.49	125710	0.66	0.47	29244	13.77	0.00	Y
Age	56.30	41.03	124636	51.84	43.17	28815	-16.45	0.00	Y

	exceedthreshold = 1			exceedthreshold = 0					
Demean by District	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.	tstat	pval	Reject?
Price	11812.42	100756.67	125710	7034.18	89251.27	29244	-7.46	0.00	Y
# Bathrooms	0.00	0.88	125710	0.01	0.89	29244	2.06	0.04	Y
# Bedrooms	-0.01	1.64	125710	-0.05	1.59	29244	-4.02	0.00	Y
Sq. ft.	-3.28	1152.21	125710	-20.82	1050.88	29244	-2.38	0.02	Y
Condo	0.01	0.38	125710	0.02	0.39	29244	5.01	0.00	Y
Single Family	-0.01	0.44	125710	-0.02	0.45	29244	-4.96	0.00	Y
Age	1.12	38.14	124636	-0.10	40.82	28815	-4.80	0.00	Y

B. Neighborhood Attributes

	exceedthreshold = 1			exceedthreshold = 0					
	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.	tstat	pval	Reject?
% Low income	28.74	23.17	614	25.12	22.44	136	-1.66	0.10	Y
% Crime	4.82E-03	4.32E-03	606	3.86E-03	3.94E-03	134	-2.38	0.02	Y
% Proficient or Advanced	59.97	19.48	614	60.85	21.48	136	0.47	0.64	N

	exceedthreshold = 1			exceedthreshold = 0					
Demean by District	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.	tstat	pval	Reject?
% Low income	1.34	5.12	614	1.23	3.75	136	-0.25	0.80	N
% Crime	-2.38E-04	1.80E-03	606	1.13E-04	1.37E-03	134	2.13	0.03	Y
% Proficient or Advanced	7.76	13.78	614	7.30	13.12	136	-0.35	0.73	N

The data shows that within districts, the means of percentage of low income and crime are higher for areas where thresholds were not exceeded. In general, neighborhoods that have better amenities will generally be associated with lower threshold levels, as by Massachusetts state definition thresholds are lower when close to a hospital, school or ground water source. This provides a possible explanation for the positive coefficient on *exceedthreshold.* To deal with this endogeneity issue, an instrumental variable approach is used, as detailed earlier in the paper, with *aquifer* being used as an instrument for *exceedthreshold.*

Although the relevance condition for *aquifer* should be satisfied, as threshold levels are dependent on distance from an aquifer by MA regulation, this can be verified in the first stage of the IV regression. The second condition for use of an instrument is the exogeneity condition, and as noted before is typically harder to justify. Table 5 shows house and district attributes for brownfields if located within 500m of an aquifer. I find that number of bathrooms, percentage of condo and single-family homes are all significantly different for houses located near an aquifer when compared to those that are not. This is reasonable due to the fact that aquifers are more likely to be located in rural areas, where space constraints are less important, minimizing the presence of condominiums. An overall summary of attribute differences can be found in Table 10 in the Appendix.

Table 5: Attributes by Threshold Exceedance

A. House Attributes

	aquifer = 1			aquifer = 0					
	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.	tstat	pval	Reject?
Price	-356.27	86512.52	57387	308.65	84432.14	66241	1.37	0.17	N
# Bathrooms	-0.01	0.82	57387	0.01	0.99	66241	3.06	0.00	Y
# Bedrooms	0.00	1.62	57387	0.00	1.66	66241	0.85	0.39	N
Sq. ft.	-2.74	1161.28	57387	2.37	1179.38	66241	0.76	0.44	N
Condo	0.01	0.36	57387	-0.01	0.38	66241	-5.85	0.00	Y
Single Family	0.00	0.43	57387	0.00	0.45	66241	3.21	0.00	Y
Age	0.05	40.43	56997	-0.04	38.59	65460	-0.38	0.70	N

B. Neighborhood Attributes

	aquifer = 1			aquifer = 0					
	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.	tstat	pval	Reject?
% Low income	-0.03	4.11	258	0.08	4.48	285	-0.13	0.89	N
% Crime	3.10E-05	2.05E-03	254	-4.40E-05	2.12E-03	278	0.43	0.67	N
% Proficient or Advanced	-0.10	17.13	258	0.11	18.72	285	-0.23	0.82	N

Note: Variables are first demeaned by district.

The results using *aquifer* as an instrument for thresholds are presented in Column (1) of Table 6, with the IV estimates in Column (2). It is shown that being located on an aquifer increases the chances of exceeding a threshold, satisfying the relevance condition. The IV estimate shows that exceeding a threshold leads to a 10.8% decline in housing price. Furthermore, while threshold exceedance is significant, the maximum toxicity value is insignificant at the 1% level, suggesting that once a threshold is exceeded, individuals are less concerned with increasing toxicities.

Table 6: Hedonic Price Regression using Instrumental Variables

	(1) First Stage	(2) IV
Dependent Variable:	exceedthreshold	log(Price)
exceedthreshold		-0.108**
		(0.0426)
aquifer	0.849***	
	(0.0437)	
maxtox	-1.04e-10*	-3.79E-12
	(0.0000)	(0.0000)
distance to Brownfield	2.40e-06	5.19e-05***
	(0.0000)	(0.0000)
# bathrooms	-0.00349	0.0896***
	(0.0023)	(0.0142)
# bedrooms	-5.11e-05	-0.00167
	(0.0009)	(0.0078)
sqft	2.25e-07	0.000117***
	(0.0000)	(0.0000)
year built	-0.0150	0.00617
	(0.0181)	(0.0085)
age	-0.0151	0.00419
	(0.0181)	(0.0086)
condo	-0.00190	0.128***
	(0.0057)	(0.0362)
single family	-0.00849	-0.228***
	(0.0098)	(0.0661)
awarded	0.566***	0.0398
	(0.0683)	(0.0310)
proposal score	-0.00204	0.00484***
	(0.0024)	(0.0015)
hazardous substances	0.167**	0.00905
	(0.0761)	(0.0440)
petroleum	0.0165	-0.0551**
	(0.0254)	(0.0257)
property size (acres)	0.0353***	0.00564
	(0.0118)	(0.0052)
% Low income	-0.00315	-0.00242

	(0.0062)	(0.0017)
% Crime	-11.10	-6.119
	(10.9047)	(4.5145)
% Proficient or Advanced	0.00361	0.000401
	(0.0038)	(0.0012)
Industrial activity nearby	0.541***	-0.0536
	(0.0878)	(0.0993)
Residential nearby	-0.309***	0.0126
	(0.0482)	(0.0237)
School nearby	-0.401***	0.0508*
	(0.0330)	(0.0251)
Green nearby	-0.391***	0.0173
	(0.0357)	(0.0263)
Constant	27.21	-8.892
	(27.6907)	(22.6718)
	64,784	64,784
R-squared	0.416	0.606
House Characteristics	X	X
Year Fixed Effects	X	X
Neighborhood Characteristics	X	X
District Fixed Effects	X	X

7 Conclusions

This paper examines the importance of conveying information to homeowners regarding severity of pollution. This is achieved by measuring housing price differentials based upon exceeding chemical threshold levels while conditioning on actual toxicity. A special feature of the way in which threshold levels are set was exploited to see exogenous variation in threshold exceedance while holding toxicity fixed. As thresholds are a binary measure and the amount over the threshold is calculable, this allows for comparison between a binary or discrete measure for information transfer. The endogeneity of thresholds necessitates the utilization of aquifer distance as an instrument to induce variation in the likelihood of exceeding a threshold.

In the fixed effects regression where the instrument was not used, exceeding a threshold, which can be interpreted as a more dangerous toxicity level, counter intuitively leads to an increase in housing values of 5% after controlling for house, time-varying neighborhood and brownfield attributes. This regression also shows that the toxicity level, as defined by the maximum concentration of an individual contaminant divided by the relevant threshold, has a negative but insignificant effect on housing prices. The positive threshold exceedance variable suggests that the estimator does not adequately control for differences in local amenities that are correlated with whether a threshold is exceeded. To verify the validity of the instrument, I examine the differences in attribute means conditional on aquifer distance. The regression results using instrumentation demonstrated a 10.8% decrease in housing transaction price if a contaminant threshold is exceeded. The estimator on maximum toxicity found at the site remains negative and insignificant.

The findings in this paper suggest that individuals respond better to information presented in a binary fashion, potentially due to ease of interpretation. I also find that thresholds used for binary categorization are negatively capitalized into housing prices, while the continuous toxicity measure is found to be statistically insignificant. Given this result, in order to develop an informed public about local pollution concerns, policy makers should carefully consider the format of information presented and its ease of interpretation.

APPENDIX

Table 7: Chemical Group by Threshold Exceedance

Chemical Group by Threshold Exceedance

Chemical Group	exceedthreshold 0	1	Total
Post Transition Metals	155	100	255
Transition Metals	707	179	886
Alkaline Earth & Alkali Metals	384	102	486
Other Elements & Asbestos	287	60	347
Aliphatics	444	154	598
Other Aromatics	947	222	1,169
Xylenes	225	29	254
3 ring PAH	661	65	726
4 ring PAH	326	119	445
5+ ring PAH	563	275	838
PCB & Oil	130	32	162
Hydrocarbons & Other organics	194	13	207
Organochlorides	580	185	765
Aromatic Organochlorides	185	21	206
Organobromides	95	4	99
Napthalenes	295	39	334
Pesticides	101	14	115
Ketone	97	11	108
Aromatics with multiple substituent groups	125	19	144
Nitro containing compounds	88	8	96
Total	6,589	1,651	8,240

Table 8: List of Site Chemicals and Frequency

Chemical	Freq	%	Chemical	Freq	%	Chemical	Freq	%
1,1,1,2 Tetrachloroethane	11	0.13	Aroclor 1221	13	0.16	Fluoranthene	152	1.84
1,1,1 Tetrachloroethane	1	0.01	Aroclor 1232	13	0.16	Fluorene	147	1.78
1,1,1 Trichloroethane	52	0.63	Aroclor 1242	15	0.18	Freon 11	2	0.02
1,1,2,2 Tetrachloroethane	14	0.17	Aroclor 1248	19	0.23	Freon 113	3	0.04
1,1,2 Trichloroethane	15	0.18	Aroclor 1250	2	0.02	Freon 114	1	0.01
1,1,2 Trichlorotrifluoroethane	2	0.02	Aroclor 1254	28	0.34	Freon 12	2	0.02
1,1 Biphenyl	1	0.01	Aroclor 1260	32	0.39	Heptachlor	7	0.08
1,1 Dichloroethane	45	0.55	Aroclor 1262	9	0.11	Heptachlor Epoxide	3	0.04
1,1 Dichloroethene	24	0.29	Aroclor 1268	8	0.1	Heptane	1	0.01
1,1 Dichloroethylene	7	0.08	Arsenic	158	1.92	Hexachlorobenzene	7	0.08
1,1 Dichloropropene	7	0.08	Asbestos	3	0.04	Hexachlorobutadiene	15	0.18
1,2,3,4,6,7,8,9 OCDD	2	0.02	Azobenzene	3	0.04	Hexachlorocyclopentadiene	1	0.01
1,2,3,4,6,7,8,9 OCDF	2	0.02	Barium	138	1.67	Hexachloroethane	4	0.05
1,2,3,4,6,7,8 HpCDD	4	0.05	Benzene	130	1.58	Indeno (1,2,3 cd) pyrene	140	1.7
1,2,3,4,7,8,9 HpCDF	2	0.02	Benzo (a) anthracene	145	1.76	Iodomethane	1	0.01
1,2,3,4,7,8 HxCDD	2	0.02	Benzo (a) pyrene	145	1.76	Iron	18	0.22
1,2,3,4,7,8 HxCDF	2	0.02	Benzo (a,e) pyrene	1	0.01	Isophorone	8	0.1
1,2,3,6,7,8 HxCDD	2	0.02	Benzo (b) fluoranthene	146	1.77	Isopropanol	1	0.01
1,2,3,6,7,8 HxCDF	2	0.02	Benzo (e) pyrene	7	0.08	Isopropyl Ether	1	0.01
1,2,3,7,8,9 HxCDD	2	0.02	Benzo (g,h,i) perylene	130	1.58	Lead	178	2.16
1,2,3,7,8,9 HxCDF	1	0.01	Benzo (j,k) Fluoranthene	1	0.01	Magnesium	13	0.16
1,2,3,7,8 PeCDD	2	0.02	Benzo (k) fluoranthene	141	1.71	Manganese	19	0.23
1,2,3,7,8 PeCDF	2	0.02	Benzoic Acid	1	0.01	Mercury	125	1.52
1,2,3 Trichlorobenzene	16	0.19	Benzyl chloride	1	0.01	Methoxychlor	5	0.06
1,2,3 Trichloropropane	8	0.1	Beryllium	80	0.97	Methyl Ethyl Ketone	2	0.02
1,2,3 Trimethylbenzene	1	0.01	Bis (2 Chloroethoxy) Methane	4	0.05	Methyl Isobutyl Ketone	6	0.07
1,2,4 Trichlorobenzene	24	0.29	Bis (2 Chloroethy) Ether	5	0.06	Methyl tert butyl ether	131	1.59
1,2,4 Trimethylbenzene	75	0.91	Bis (2 Ethyhexyl) phthalate	15	0.18	Methylene Chloride	33	0.4
1,2 Dibromo 3 Chloropropane	8	0.1	Bis (2 Ethylhexyl) phthalate	2	0.02	Motor Oil	1	0.01
1,2 Dibromoethane	12	0.15	Bromobenzene	10	0.12	N Nitrosodiphenylamine	2	0.02
1,2 Dichlorobenzene	32	0.39	Bromochloromethane	10	0.12	Naphthalene	210	2.55
1,2 Dichloroethane	21	0.25	Bromodichloromethane	13	0.16	Nickel	102	1.24
1,2 Dichloropropane	15	0.18	Bromoform	14	0.17	Nitrate	1	0.01
1,2 Diphenylhydrazine	1	0.01	Bromomethane	16	0.19	Nitrite	1	0.01
1,2 dichloropropane	1	0.01	Butylbenzylphtalate	7	0.08	Nitrobenzene	4	0.05
1,3,5 Trimethylbenzene	69	0.84	C10 C28 Medium Petroleum Distillate	1	0.01	Pentachlorophenol	12	0.15
1,3 Butadiene	3	0.04	C11 C22 Aromatics	179	2.17	Perchloroethylene	1	0.01
1,3 Dichlorobenzene	26	0.32	C13 C16 Aliphatics	1	0.01	Perylene	5	0.06
1,3 Dichloropropane	7	0.08	C16 C36 Heavy Petroleum Distillate	1	0.01	Pesticides	3	0.04
1,4 Dichlorobenzene	38	0.46	C19 C22 Aromatics	1	0.01	Phenanthrene	161	1.95
1,4 Dioxane	8	0.1	C19 C36 Aliphatics	174	2.11	Phenol	7	0.08

1 Methylnaphthalene	12	0.15	C5 C10 Aromatics	2	0.02	Phosphorus	1	0.01
2,2 Dichloropropane	7	0.08	C5 C8 Aliphatics	127	1.54	Potassium	9	0.11
2,2 Oxybis (1 Chloropropane)	3	0.04	C6 C12 Light Petroleum Distillate	1	0.01	Propylene	1	0.01
2,3,4,6,7,8 HxCDF	2	0.02	C6 C36 Aromatics	2	0.02	Pyrene	154	1.87
2,3,4,7,8 PeCDF	2	0.02	C6 C8 Aliphatics	2	0.02	Pyridine	2	0.02
2,3,7,8 TCDD	2	0.02	C9 C10 Aromatics	128	1.55	Selenium	105	1.27
2,3,7,8 TCDD TEQ	1	0.01	C9 C12 Aliphatics	128	1.55	Silver	117	1.42
2,3,7,8 TCDF	2	0.02	C9 C18 Aliphatics	165	2	Sodium	9	0.11
2,4,5 Trichlorophenol	6	0.07	C9 C36 Aliphatics	1	0.01	Styrene	17	0.21
2,4,6 Trichlorophenol	5	0.06	Cadmium	135	1.64	Sulfate	1	0.01
2,4 Dichlorophenol	4	0.05	Calcium	9	0.11	Tetrachlorethene	64	0.78
2,4 Dimethylphenol	6	0.07	Carbazole	10	0.12	Tetrachloroethylene	18	0.22
2,4 Dinitrophenol	4	0.05	Carbon Disulfide	14	0.17	Tetrahydrofuran	8	0.1
2,4 Dinitrotoluene	4	0.05	Carbon Tetrachloride	13	0.16	Thallium	68	0.83
2,6 Dimethylnaphthalene	3	0.04	Chlordane	2	0.02	Toluene	147	1.78
2,6 Dinitrotoluene	4	0.05	Chlorobenzene	29	0.35	Trichloro fluoro methane	2	0.02
2 Butanone	26	0.32	Chlorodibromomethane	3	0.04	Trichloroethene	62	0.75
2 Chloronaphthalene	8	0.1	Chloroethane	20	0.24	Trichloroethylene	20	0.24
2 Chlorophenol	4	0.05	Chloroform	21	0.25	Trichlorofluoromethane	9	0.11
2 Chlorotoluene	9	0.11	Chloromethane	15	0.18	Vanadium	69	0.84
2 Hexanone	12	0.15	Chromium	151	1.83	Vinyl Acetate	5	0.06
2 Methylnaphthalene	159	1.93	Chrysene	146	1.77	Vinyl Chloride	42	0.51
2 Methylphenol	5	0.06	Cobalt	8	0.1	Xylene	92	1.12
2 Nitroaniline	2	0.02	Copper	50	0.61	Zinc	109	1.32
2 Nitrophenol	4	0.05	Cyanide	29	0.35	alpha BHC	4	0.05
3,3 Dichlorobenzidine	4	0.05	Cyclohexane	1	0.01	alpha Chlordane	4	0.05
3 Nitroaniline	2	0.02	Di n Butylphthalate	13	0.16	beta BHC	5	0.06
4,4' DDD	9	0.11	Di n Octylphthalate	6	0.07	bis (2 Chloroisopropyl) Ether	1	0.01
4,4' DDE	9	0.11	Dibenzo (a,h) anthracene	127	1.54	cis 1,2 Dichloroethene	45	0.55
4,4' DDT	11	0.13	Dibenzofuran	18	0.22	cis 1,2 Dichloroethylene	10	0.12
4,6 Dinitro 2 Methylphenol	2	0.02	Dibenzothiophene	2	0.02	cis 1,3 Dichloropropene	13	0.16
4 Isopropyltoluene	1	0.01	Dibromochloromethane	10	0.12	cis Dichloroethene	8	0.1
4 Bromophenyl phenylether	4	0.05	Dibromoethane	1	0.01	delta BHC	2	0.02
4 Chloro 3 Methylphenol	2	0.02	Dibromomethane	6	0.07	gamma BHC	3	0.04
4 Chloroaniline	4	0.05	Dichlorodifluoromethane	12	0.15	gamma Chlordane	6	0.07
4 Chlorophenyl Phenyl Ether	2	0.02	Dichloromethane	1	0.01	isopropylbenzene	54	0.66
4 Chlorotoluene	11	0.13	Dieldrin	11	0.13	m/p Cresol	1	0.01
4 Ethyltoluene	1	0.01	Diethyl Ether	4	0.05	m/p Xylene	86	1.04
4 Isopropylbenzene	1	0.01	Diethylphthalate	6	0.07	n Butylbenzene	49	0.59
4 Isopropyltoluene	23	0.28	Diisopropyl Ether	6	0.07	n Hexane	1	0.01
4 Methyl 2 Pentanone	9	0.11	Dimethylphthalate	4	0.05	n Nitroso di n Propylamine	2	0.02
4 Methylphenol	5	0.06	Dioxins	5	0.06	n Propylbenzene	59	0.72
4 Nitroaniline	2	0.02	Endosulfan	1	0.01	o Chlorotoluene	1	0.01
4 Nitrophenol	3	0.04	Endosulfan I	3	0.04	o Cresol	1	0.01
4 nitrophenol	1	0.01	Endosulfan II	3	0.04	o Xylene	76	0.92

Acenaphthene	140	1.7	Endosulfan Sulfate	1	0.01	p Chlorotoluene	1	0.01
Acenaphthylene	132	1.6	Endosulfan sulfate	1	0.01	p Isopropyltoluene	27	0.33
Acetone	40	0.49	Endrin	3	0.04	sec Butylbenzene	51	0.62
Acetophenone	5	0.06	Endrin Aldehyde	1	0.01	tert Amyl Methyl Ether	7	0.08
Aldrin	3	0.04	Endrin Ketone	4	0.05	tert Butylalcohol	1	0.01
Aluminum	9	0.11	Ethanol	1	0.01	tert Butylbenzene	19	0.23
Aniline	5	0.06	Ether	2	0.02	tert Butylethyl Ether	3	0.04
Anthracene	146	1.77	Ethyl Acetate	1	0.01	trans 1,2 Dichloroethene	21	0.25
Antimony	81	0.98	Ethyl Ether	1	0.01	trans 1,2 Dichloroethylene	9	0.11
Aroclor	5	0.06	Ethyl tert butyl Ether	3	0.04	trans 1,3 Dichloropropane	1	0.01
Aroclor 1016	13	0.16	Ethylbenzene	150	1.82	trans 1,3 Dichloropropene	12	0.15

Table 9: Brownfield & Assessment Summary Statistics

Brownfield Attributes

Variable	N	mean	p50	sd	min	max
Awarded	58	0.79	1.00	0.41	0.00	1.00
Proposal Score	56	94.13	96.00	14.14	53.00	118.00
Hazardous Substance	58	0.83	1.00	0.38	0.00	1.00
Petroleum	58	0.24	0.00	0.43	0.00	1.00
property size (acres)	54	4.49	1.55	6.29	0.02	27.00

Assessment Results

Variable	Obs.	Mean	Median	St. Dev.	Min.	Max
Samples Taken	262	31.45	28.00	25.79	1.00	162.00
maxconcentration	262	4461.94	3.92	32329.32	0.00	460000
Threshold Value	262	12947.91	300.00	80511.96	0.01	1000000
Soil	262	0.56	1.00	0.50	0.00	1.00
Groundwater	262	0.39	0.00	0.49	0.00	1.00
Other (air, surface water, sediment)	262	0.05	0.00	0.21	0.00	1.00

Table 10: Summary of Attribute Differences

	By Exceed Threshold		Demean		By Aquifer Demean	
Characteristics	t-stat	Reject?	t-stat	Reject?	t-stat	Reject?
Price	**-25.77**	**Y**	**-7.46**	**Y**	1.37	N
# Bathrooms	-1.61	N	**2.06**	**Y**	**3.06**	**Y**
# Bedrooms	**-4.53**	**Y**	**-4.02**	**Y**	0.85	N
Sq. ft.	-0.88	N	**-2.38**	**Y**	0.76	N
Condo	**-5.99**	**Y**	**5.01**	**Y**	**-5.85**	**Y**
Single Family	**13.77**	**Y**	**-4.96**	**Y**	**3.21**	**Y**
Age	**-16.45**	**Y**	**-4.80**	**Y**	-0.38	N
PWS					0.03	N
% Low income	**-1.66**	**Y**	-0.25	N	-0.13	N
% Crime	**-2.38**	**Y**	**2.13**	**Y**	0.43	N
% Proficient or Advanced	**0.47**	**Y**	-0.35	N	-0.23	N

Note: Rejection of the Null that differences in means across groups are equal are denoted in **Bold**.

Works Cited

"310 CMR 40: Massachusetts Contingency Plan, Subpart I: Risk Characterization." Massachusetts Department of Environmental Protection. 2013. Accessed: March 4, 2013. http://www.mass.gov/dep/cleanup/laws/mcpsubi.htm

Alberini, Anna, et al. "The role of liability, regulation and economic incentives in brownfield remediation and redevelopment: evidence from surveys of developers." *Regional Science and Urban Economics* 35.4 (2005): 327-351.

Bartsch, Charles, and Elizabeth Collaton. *Brownfields: Cleaning and reusing contaminated properties*. Westport, CT: Praeger, 1997.

Bishop, Kelly C., and Christopher Timmins. *Hedonic Prices and Implicit Markets: Estimating Marginal Willingness to Pay for Differentiated Products Without Instrumental Variables*. No. w17611. National Bureau of Economic Research, 2011.

"Brownfields and Land Revitalization." U.S. Environmental Protection Agency. 02/27/2013. Accessed: 02/28/2013. http://www.epa.gov/brownfields/index.html

Bui, L. T. and Mayer, C. J. (2003), "Regulation and capitalization of environmental amenities: Evidence from the toxic release inventory in Massachusetts," Review of Economics and statistics, 85, 693-708.

Carroll, Thomas M., Terrence M. Clauretie, and Jeff Jensen. "Living next to godliness: Residential property values and churches." *The Journal of Real Estate Finance and Economics* 12.3 (1996): 319-330.

Decker, C. S., Nielsen, D. A., and Sindt, R. P. (2005), "Residential Property Values and Community Right-to-Know Laws: Has the Toxics Release Inventory Had an Impact?" Growth and Change, 36, 113-133.

EPA, U. (2012), "Brownfield and Land Revitalization," Available at http://www.epa.gov/brownfields, (assessed October 2013).

EPA, U. (2014), "Emergency Planning and Community Right to Know Act (EPCRA)," Available at http://www2.epa.gov/epcra-tier-i-and-tier-ii-reporting/what-epcr, Accessed: March 2014.

"Encyclopedia: Pollution." Green U Student, Junior Media LLC. 2013. Accessed: March 3, 2013. http://www.greenstudentu.com/encyclopedia/pollution

Gawande, K. and Jenkins-Smith, H. (2001), "Nuclear waste transport and residential property values: estimating the effects of perceived risks," Journal of Environmental Economics and Management, 42, 207-233.

Gayer, T. and Viscusi, K. W. (2002), "Housing price responses to newspaper publicity of hazardous waste sites," Resource and Energy Economics, 24, 33-51.

Gayer, Ted, James T. Hamilton, and W. Kip Viscusi. "Private values of risk tradeoffs at superfund sites: housing market evidence on learning about risk." *Review of Economics and Statistics* 82.3 (2000): 439-451.

"Geographic Terms and Concepts - School Districts." *United States Census Bureau*. United States Census Bureau, 6 Dec. 2012. Web. 03 Dec. 2013. <http://www.census.gov/geo/reference/gtc/gtc_sd.html>.

Gra_ Zivin, J. and Neidell, M. (2009), "Days of haze: Environmental information disclosure and intertemporal avoidance behavior," Journal of Environmental Economics and Management, 58, 119-128.

Gra_ Zivin, J., Neidell, M., and Schlenker, W. (2011), "Water quality violations and avoidance behavior: Evidence from bottled water consumption," in American Economic Review: Papers and Proceedings, vol. 101, pp. 448-453.

Greenberg, M et al. "Brownfields, Toads, and the Struggle for Neighborhood Redevelopment: A Case Study of the State of New Jersey." Urban Affairs Review, 35, p717-733.

Hamilton, J. T. (1995), "Pollution as news: media and stock market reactions to the toxics release inventory data," Journal of environmental economics and management, 28, 98-113.

Haninger, K et al. "Estimating the Impacts of Brownfield Remediation on Housing Property Values: Working Paper." Nicholas Institute for Environmental Policy Solutions, Duke University. 2012.

Hite, Diane, et al. "Property-value impacts of an environmental disamenity: the case of landfills." *The Journal of Real Estate Finance and Economics* 22.2 (2001): 185-202.

Kaufman, Dennis A., and Norman R. Cloutier. "The impact of small brownfields and greenspaces on residential property values." *The Journal of Real Estate Finance and Economics* 33.1 (2006): 19-30.

Khanna, M. and Damon, L. A. (1999), "EPA's voluntary 33/50 program: impact on toxic releases and economic performance of firms," Journal of environmental economics and management, 37, 1{25.

Konar, S. and Cohen, M. A. (1997), "Information as regulation: the effect of community right to know laws on toxic emissions," Journal of environmental Economics and Management, 32, 109-124.

Lancaster, Kelvin J. "A New approach to consumer theory" *Journal of Political Economy.* 74 (1966): 132- 157.

Leigh, Nancey Green, and Sarah L. Coffin. "Modeling the relationship among brownfields, property values, and community revitalization." *Housing Policy Debate* 16.2 (2005): 257-280.

Ma, L. (2014), "Learning in a Hedonic Framework: Valuing Brownfield Remediations,"Working Paper.

MassGIS (2014) Available at http://www.mass.gov/anf/research-and-tech/it-serv-and-support/application-serv/office-of-geographic-information-massgis, (assessed March 2014).

McClelland, G. H., Schulze, W. D., and Hurd, B. (1990), "The Effect of Risk Beliefs on Property

Values: A Case Study of a Hazardous Waste Site1," Risk analysis,10, 485-497.

Mundy, Bill. “Stigma and. Value,” The Appraisal Journal, January 1992: 7-13

Oberholzer-Gee, F. and Mitsunari, M. (2006), “Information regulation: Do the victims of externalities pay attention?" Journal of Regulatory Economics, 30, 141-158.

of Environmental Protection, M. D. (2009), “Massachusetts Contingency Plan," Available at http://www.mass.gov/dep/cleanup/laws/regulati.htm, (Accessed: October 2013).

Patchin, P. “Valuation of Contaminated Properties,” The Appraisal Journal, 56(1):7-16, January 1988.

Patchin, P. “Contaminated Properties- Stigma Revisited,” The Appraisal Journal, 59(2): 167- 173, April 1991a.

Paull, Evans. "The environmental and economic impacts of brownfields redevelopment." *Northeast–Midwest Institute (www. nemw. org)* (2008).

Pepper, E., 1997. Lessons from the Field: Unlocking Economic Potential with an Environmental key. Northeast-Midwest Institute, Washington, DC.

Powers, N. E. (2013), “Measuring The Impact Of The Toxics Release Inventory: Evidence From Manufacturing Plant Births," Tech. rep.

Rakestraw, C. "‘An evaluation of the risk-based approach to brownfield remediation and development." *Master's project, Master of Environmental Management Duke University* (2000).

Ridker, Ronald G., and Henning, John A. "The Determinants of Residential Property Values with Special Reference to Air Pollution." Rev. Econ. and Statis.49 (May1967): 246-57. (2)

Rosen, Sherwin. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." J.P.E.82 (January/February 1974): 34-55.

Sanders, N. J. (2013), “Toxic Assets: How the Housing Market Responds to Environmental Information Shocks," Under Review.

Smith, V. K. and Johnson, F. R. (1988), “How do risk perceptions respond to information? The case of radon," The Review of Economics and Statistics, 70, 1-8.

Taylor, L.O. (2003). “The Hedonic Method.” In A Primer on Nonmarket Valuation of the Environment. , ed. T. Brown P. Champ and K. Boyle. Dordrecht: Kluwer Academic Publishers.

Viscusi, W. K., Magat, W. A., and Huber, J. (1986), “Informational regulation of consumer health risks: an empirical evaluation of hazard warnings," The Rand Journal of Economics, pp. 351-365.